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A Meteorological Information Mining-Based Wind Speed Model for Adequacy Assessment of Power Systems With Wind Power

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Abstract

Accurate wind speed simulation is an essential prerequisite to analyze the power systems with wind power. A wind speed model considering meteorological conditions and seasonal variations is proposed in this paper. Firstly, using the path analysis method, the influence weights of meteorological factors are calculated. Secondly, the meteorological data are classified into several states using an improved Fuzzy C-means (FCM) algorithm. Then the Markov chain is used to model the chronological characteristics of meteorological states and wind speed. The proposed model was proved to be more accurate in capturing the characteristics of probability distribution, auto-correlation and seasonal variations of wind speed compared with the traditional Markov chain Monte Carlo (MCMC) and autoregressive moving average (ARMA) model. Furthermore, the proposed model was applied to adequacy assessment of generation systems with wind power. The assessment results of the modified IEEE-

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RTS79 and IEEE-RTS96 demonstrated the effectiveness and accuracy of the proposed model.

Keywords: Adequacy assessment, clustering analysis, Markov chain, meteorological factors, wind speed model.

1. Introduction

Energy consumption has been heavily dependent on fossil fuels for a long time, which causes problems such as resource depletion, climate change and environmental pollution. Wind power is considered as an alternative to fossil fuels in order to alleviate these problems. However, the stochastic nature of wind power poses challenges to power systems. Incorporating wind power into reliability assessment requires accurate modeling. The effect of wind power on reliability assessment is highly dependent on the characteristics of wind such as statistical characteristics (probability distribution) and time evolution characteristics (auto-correlation) [1]. Therefore, it is important to utilize an appropriate wind speed model to represent wind power variation characteristics in order to obtain accurate results in reliability assessment.

There are two main types of wind speed models: probabilistic models [2-4] and time series models [5-14]. Weibull distribution [2-3] and Rayleigh distribution [4] are most widely used in probabilistic models which can reflect the statistical characteristics of wind speed. However, the time evolution characteristics of wind speed are neglected in these probabilistic models. At present, the time series models are more widely used in reliability assessment studies. The stochastic process theory based models are mainly divided into two types: autoregressive moving average (ARMA) models [5-6] and Markov Chain Monte Carlo (MCMC) models [7-9]. The temporal auto-correlation of wind speed can be modelled in the ARMA models. However, these models cannot guarantee a good fit of the statistical characteristics. The probability distribution of the wind speed samples generated by ARMA models may be a normal distribution and negative wind speed samples are generated. And in the ARMA models, the wind speed data should be stationary and invertible. MCMC models represent the wind speed with a finite number of states. The probabilities in each state are assumed to be uniformly distributed, which can cause errors. The MCMC models represent time evolution characteristics using a transition matrix. Improved models such as the semi-Markov model [10] and Bayesian Markov model [11] show better accuracy in capturing time evolution characteristics. A two-tier reliability model is proposed in [12], which models the weather types and wind power fluctuations by Markov chains, respectively. Besides, models such as the two-dimensional wind speed statistical model [13] and time-dependent clustering model [14] are developed for reliability assessment.

The wind speed models proposed in the literatures are based on measured wind speed data with specific resolutions such as 10min, 15 min or 1 hour. They can describe the wind speed characteristics of the specific time resolutions. However, the wind speed characteristics for longer time scales cannot be captured. Moreover, the seasonal variations are not taken into consideration in these models. The seasonal factors should be considered to obtain accurate results in long-term reliability assessment [9]. Thus, a meteorological information mining-based wind speed model for reliability assessment is proposed in this paper. The meteorological conditions and seasonal variations are considered in this model. As such, the characteristics of wind speed can be accurately modelled for longer time scales and the seasonal characteristics can be represented. Firstly, the influence weights of meteorological factors on wind power output are calculated using the path analysis method. Secondly, using an improved Fuzzy C-means

(FCM) clustering algorithm, the daily meteorological states are obtained. Then, a two-step MCMC model is developed to model the meteorological conditions and wind speed: the first step is the meteorological state time series simulation considering the seasonal variations; and the second step is the wind speed time series simulation within a specific meteorological state. The empirical distribution function of wind speed is used in the second step to improve the probabilistic accuracy of each state in the model. The proposed model is validated from the probability distribution and auto-correlation. The modified IEEE RTS79 and IEEE-RTS96 with wind power were used to demonstrate the effectiveness of the proposed model for reliability assessment.

The rest of the paper is organized as follows. The classification method is presented in Section 2. The two-step MCMC model is proposed in Section 3. The parameters of the traditional MCMC model and ARMA model used for comparison are presented in Section 4. In Section 5, the proposed model is verified by comparing with the traditional MCMC model and ARMA model. The effectiveness of the proposed model for reliability assessment is demonstrated in Section 6, followed by conclusions.

2. Classification methodology of meteorological states

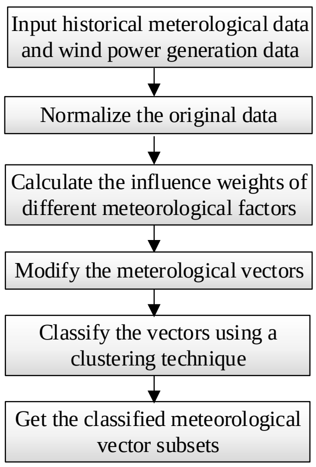


Fig. 1. Flow chart of classification methodology of meteorological states

The meteorological factors have significant effects on the wind power output. In this paper, the meteorological factors such as wind speed, wind direction, temperature, atmospheric pressure and precipitation are represented by an n-dimensional vector $\boldsymbol{X}=[x_1,x_2,...,x_n]$. The characteristics of wind power output are represented by the daily power generation y. The overall process of classification is illustrated in Fig.1. The meteorological data and daily power generation data are normalized firstly. Then, the influence weights of the meteorological factors are calculated using the path analysis method. A clustering technique is used to classify the multi-dimensional vectors.

2.1. Data Normalization

The daily meteorological dataset and power generation dataset of a wind farm can be denoted as a matrix:

$$\boldsymbol{Z}=[\boldsymbol{X},\boldsymbol{Y}]=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} & y_1 \\ x_{21} & x_{22} & \cdots & x_{2n} & y_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Nn} & y_N \end{bmatrix} \tag{1}$$

where x and y are the meteorological data and power generation data, respectively; n is the number of meteorological factors; N is the total number of days.

The original data have different units. In order to eliminate the effects of the units on the classification results, the original data should be normalized to the values in the interval [0, 1] by,

$$z_{ij}^*=\frac{z_{ij}-z_j^{\min}}{z_j^{\max}-z_j^{\min}} \tag{2}$$

where z_{ij} and z_{ij}^* are the original and normalized elements of matrix $\boldsymbol{Z}$, $z_j^{\min}$ and $z_j^{\max}$ are the minimum and maximum elements of $j\text{th}$ column of matrix $\boldsymbol{Z}$, respectively.

2.2. Calculation of influence weights

Since the effects of meteorological factors on wind power output are quite different, the differences should be considered and represented by influence weights.

The path analysis method is widely used to identify the correlation between multiple variables, which is an extension of the multiple linear regression analysis [15]. The path coefficients are used to represent the links between independent and dependent variables. The conventional multiple linear regression model is shown as,

$$y^* = b_0 + b_1 x_1^* + b_2 x_2^* + \cdots + b_n x_n^* \tag{3}$$

where $b_i \ (i = 1, 2, ..., n)$ are the partial regression coefficients; x^* and y^* are the normalized meteorological data and daily power generation, respectively.

The direct path coefficients are considered in this paper, which are defined as,

$$E_{x_i^* \to y^*} = b_i \sqrt{\sum_{j=1}^{N} \left(x_{ji}^* - \overline{x_i^*} \right) / \sum_{j=1}^{N} \left(y_j^* - \overline{y^*} \right)} \ , \ i = 1, 2, ..., n \tag{4}$$

Then, the influence weights of meteorological factors can be calculated by [16],

$$\omega_i = \frac{\left| E_{x_i^* \to y^*} \right|}{\sum_{j=1}^{n} \left| E_{x_j^* \to y^*} \right|} \tag{5}$$

Thus, the normalized meteorological vector modified by the influence weights is,

$$\boldsymbol{X}_\omega^* = \left[\omega_1 x_1^*, \omega_2 x_2^*, ..., \omega_n x_n^* \right] \tag{6}$$

2.3 Classification of meteorological states

To recognize typical meteorological states, the modified meteorological vectors are divided into C sets using the clustering technique. Clustering algorithms can be categorized by the principle (objective function, graph-theoretical, hierarchical) or the model type (deterministic, probabilistic, and fuzzy) [8]. The FCM algorithm is one of the most widely used unsupervised clustering algorithms, first proposed by Dunn in

1974 and improved by Bedzek [17]. It is an improved hard k-means algorithm, which aims to minimize the distance between elements and cluster centers.

Let $\boldsymbol{X}=\{X_1,X_2,...,X_N\}\subset \mathrm{R}^n$ be the unclassified dataset and $\boldsymbol{V}=\{V_1,V_2,..., V_C\}\subset \mathrm{R}^n$ denotes the cluster centers. The objective function of the FCM algorithm is defined as,

$$J(\boldsymbol{U},\boldsymbol{V})=\sum_{i=1}^{N}\sum_{j=1}^{C}\mu_{ij}^{m}\|X_i-V_j\|^2,\ \ 1\leqslant m<\infty \tag{7}$$

where m denotes the index of fuzziness, $\|\cdot\|$ denotes the Euclidean distance between the data point X_i and cluster center V_j. The matrix $\boldsymbol{U}=[u_{ij}]_{N\times C}$ is a fuzzy partition matrix of u_{ij} which is the membership value of vector X_i in the $j\mathrm{th}$ cluster with the cluster center V_j. The membership should meet the constraints of,

$$\sum_{j=1}^{C}u_{ij}=1,\ \ 0\leqslant u_{ij}\leqslant 1,\ \ \forall i\in 1,2,...,N. \tag{8}$$

The optimization problem can be solved using the iterative algorithm. The cluster centers and fuzzy partition matrix for $k\mathrm{th}$ iteration can be obtained by,

$$V_j^{(k)}=\frac{\sum_{i=1}^{N}(u_{ij}^{(k)})^m X_i}{\sum_{i=1}^{N}(u_{ij})^m} \tag{9}$$

$$u_{ij}^{(k)}=\frac{1}{\sum_{l=1}^{C}\left[\frac{\|X_i-V_j\|}{\|X_i-V_l\|}\right]^{\frac{2}{m-1}}} \tag{10}$$

The convergence condition of this iterative process is defined by,

$$\|\boldsymbol{U}^{(k)}-\boldsymbol{U}^{(k-1)}\|<\varepsilon. \tag{11}$$

The conventional FCM algorithm is extremely sensitive to the initial cluster centers.

To avoid this drawback, an improved FCM algorithm (called the global FCM algorithm) is proposed in this paper. The global FCM algorithm proceeds in an incremental way: to solve the problem with C clusters, all intermediate problems with $1, 2, \ldots, C-1$ clusters are sequentially solved. The proposed method is briefly described as follows.

Step 1) Start with $c=1$ and find the one cluster center using the conventional FCM algorithm.

Step 2) Let $\{V_{1*}^{(c-1)}, V_{2*}^{(c-1)}, \ldots, V_{N*}^{(c-1)}\}$ denotes the final solution of the $(c-1)$ -clustering problem. N times of the FCM algorithm are executed with c clusters where each run i $(i=1, 2, \ldots, N)$ starts from the initial state $\{V_{1*}^{(c-1)}, V_{2*}^{(c-1)}, \ldots, V_{N*}^{(c-1)}, X_i\}$. The optimal solution of N runs is considered as the solution $\{V_{1*}^{(c)}, V_{2*}^{(c)}, \ldots, V_{N*}^{(c)}\}$ of the c -clustering problem.

Step 3) Repeat Step 2) until the optimal C clusters are obtained.

The cluster to which a data vector belongs depends on their maximum membership.

3. Modelling of wind speed

3.1 Markov Chain

A Markov Chain is a special type of discrete-time stochastic process which describes the random movement among a finite number of states. It is a stochastic process without memory, which means that the process going from state i to state j depends only on the state at time t, not on the previous states leading to the state at time t.

Let X denote a Markov Chain. Suppose the state space includes K states $\{1, 2, \ldots, K\}$, the state transition probability from state i to state j,

$$\mathrm{Prob}(X_{t+1}=j \mid X_t=i) = p_{ij} \tag{12}$$

is a constant in the process. Then the Markov Chain model can be defined by a $K \times K$ transition probability matrix,

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1K} \\ p_{21} & p_{21} & \cdots & p_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ p_{K1} & p_{K2} & \cdots & p_{KK} \end{bmatrix} \tag{13}$$

Each row of the matrix corresponds to the current state, while each column is the possible next state. The sum of the transition probabilities at each row is 1. The maximum likelihood estimate of the matrix is,

$$p_{ij} = \frac{N_{ij}}{\sum_{k=1}^{K} N_{ik}} \tag{14}$$

where N_{ij} is the number of transitions from state i to state j encountered in the record.

The simulation of the MCMC model is performed by first constructing the cumulative probability matrix $\boldsymbol{P}_{\text{cum}}$. Each row i of $\boldsymbol{P}_{\text{cum}}$ corresponds to the discrete cumulative distribution function for the next transition. Thus, in the matrix $\boldsymbol{P}_{\text{cum}}$, $p_{\text{cum},ij}$ is defined as,

$$p_{\text{cum},ij} = \begin{cases} 0, & \text{if } j = 1, \\ \sum_{k=1}^{K} p_{ik}, & \text{if } 1 < j \leqslant K+1. \end{cases} \tag{15}$$

3.2 Two-step MCMC model for wind speed simulation

1) Meteorological state simulation

Suppose the meteorological data are classified into K_{MS} states. Considering seasonal variations, the transition matrixes are calculated for each month. The cumulative probability matrix is denoted by $\boldsymbol{P}_{m,ij}^{\text{MS\_cum}}$, where m $(m = 1, 2, ..., 12)$ denotes the month of a year. The following simulation process is performed to generate a meteorological state series.

Step 1) An initial meteorological state is randomly given according to the current month (mth month).

Step 2) Assume that the current state is state i, a random variable r, which follows a uniform distribution in the interval $[0, 1]$, is generated and compared with the element of the ith row of the matrix $\boldsymbol{P}_{m,ij}^{\mathrm{MS\_cum}}$. If r is between the elements j and $j+1$ ($p_{m,ij}^{\mathrm{MS\_cum}} < r < p_{m,ij}^{\mathrm{MS\_cum}}$), the state j will be selected as the next meteorological state.

Step 3) Repeat Step 2) for a specific number of days according to the current month.

Step 4) Repeat Step 1) to Step 3) for a given number of years. So, the meteorological state time series can be obtained.

2) Intraday wind speed simulation

Similarly, the intraday wind speed simulation is based on the cumulative wind speed state transition matrix $\boldsymbol{P}_{k}^{\mathrm{WS\_cum}}$ $(k = 1, 2, ..., K_{\mathrm{MS}})$ for the meteorological state k. In the traditional MCMC model, the wind speed is considered as uniformly distributed within each state, which can lead to errors. In this paper, the empirical distribution function f_{cdf} of wind speed is utilized to modify the probability distribution within each state. The following process is performed to simulate an intraday wind speed time series for a specific meteorological state k.

Step 1) An initial wind speed state is randomly given according to the current meteorological state.

Step 2) Suppose the current wind speed state is state i, a random variable r_1, which is uniformly distributed in [0, 1], is generated and compared with the element of the ith row of the matrix $\boldsymbol{P}_k^{\mathrm{WS\_cum}}$ ($k=1, 2, ..., K_{\mathrm{WS}}$). If r_1 is between the elements j and $j+1$ ($p_{k,ij}^{\mathrm{WS\_cum}} < r_1 \leqslant p_{k,i(j+1)}^{\mathrm{WS\_cum}}$), the state j will be selected as the next wind speed state.

Step 3) A random variable r_2, which follows a uniform distribution in the interval [0, 1], is generated and then the wind speed sample V can be obtain by,

$$f_{\mathrm{cdf}}(V) = f_{\mathrm{cdf}}(V_j^{\min}) + r_2 \times \left(f_{\mathrm{cdf}}(V_j^{\max}) - f_{\mathrm{cdf}}(V_j^{\max})\right) \tag{16}$$

$$V = V_S + \frac{f_{\mathrm{cdf}}(V) - f_{\mathrm{cdf}}(V_S)}{f_{\mathrm{cdf}}(V_{S+1}) - f_{\mathrm{cdf}}(V_S)} \left(V_{S+1} - V_S\right) \tag{17}$$

where $V_j^{\min}$ and $V_j^{\max}$ are the lower and upper limits of state j, respectively, and S denotes the subscript of the corresponding element in the discrete empirical distribution function f_{cdf} (i.e., $f_{\mathrm{cdf}}(V_S) \leqslant f_{\mathrm{cdf}}(V) < f_{\mathrm{cdf}}(V_{S+1})$).

Step 4) Repeat Step 2) and Step 3) for a given length of time. An intraday wind speed time series is obtained for the meteorological state k.

Step 5) Repeat Step 1) to Step 4) until the entire wind speed time series corresponding to the meteorological state series generated before.

4. Parameters of the Traditional MCMC Model and ARMA Model

To demonstrate the effectiveness of the proposed model, the proposed model is compared with the ARMA model and traditional MCMC model in this paper.

The number of wind speed states in the proposed model is eight ($K_{\mathrm{WS}}=8$). Consequently, an eight-state traditional MCMC model is developed. Moreover, an ARMA model is built using the same wind speed data. For the ARMA model, an ARMA (4, 3) model is regarded as the optimal time series model for this site. The parameters are,

$$
\begin{aligned}
y_t = & 0.6893 y_{t-1} + 0.4023 y_{t-2} - 0.2322 y_{t-3} \\
& + 0.0654 y_{t-4} + \alpha_t + 0.5658 \alpha_{t-1} - 0.1080 \alpha_{t-2} \\
& - 0.0058 \alpha_{t-3}, \qquad \alpha_t \in \mathrm{NID}\left(0, 0.2825^2\right)
\end{aligned} \tag{18}
$$

where y_t is the time series value at time t and α_t is a white normal noise process.

Thus, the desired wind speed sample SW_t at time t can be obtained by,

$$SW_t = \mu_t + \sigma_t y_t \tag{19}$$

where μ_t and σ_t are the mean and standard deviation of historical wind speed data, respectively.

5. Case Studies

The measured wind power and meteorological data of a wind farm located in northern China are used to perform case studies to verify the meteorological information mining based wind speed model. The wind farm comprises of 24 wind turbine generators with rated power of 2 MW. Nine available meteorological factors are chosen to form the meteorological vector including the daily average wind speed $\bar{V}$, wind direction d, max-temperature $T_{\max}$, min-temperature $T_{\min}$, average temperature T_{avg}, atmospheric pressure P, humidity H, precipitation I and solar irradiation G. The wind power and meteorological data were obtained from the real wind farm and the public weather website from 2012 to 2014. The wind power and wind speed data are recorded every 10 min.

To evaluate these models, the probability density function (PDF) and auto-correlation function (ACF) are used to represent the probability distribution and time evolution characteristics of wind speed, respectively. In addition to the wind speed samples with 10-min temporal resolution, considering the significance of daily average wind power output of wind farms in power system planning and operation, the characteristics of daily average wind power output are also discussed in this paper. The root mean square error (RMSE) [18] is utilized to measure the differences of PDF and ACF curves of the measured and simulated results.

5.1 Classification results of meteorological states

The influence weights of nine meteorological factors are calculated by using the path analysis method and are listed in Table 1. It can be seen that the daily average wind speed and temperature are the most significant meteorological factors affecting the daily wind generation.

Table 1

Influence weights of different meteorological factors.

Meteorological Factor	$\bar{V}$	d	$T_{\max}$	$T_{\min}$	T_{avg}	P	H	I	G
Influence Weights	0.6414	0.0052	0.0446	0.1247	0.1098	0.0161	0.0345	0.0007	0.0230

As shown in Fig. 2, the objective function value is reduced by increasing the number of clusters. However, this reduction becomes insignificant when the number of clusters is six or more. Thus, it can be concluded that a six-cluster model ($K_{\text{MS}} = 6$) is suitable.

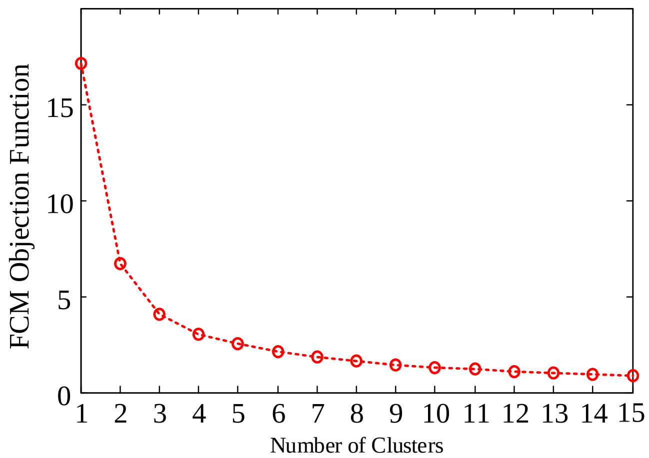


Fig. 2. The relationship between the number of clusters and the FCM objective function value.

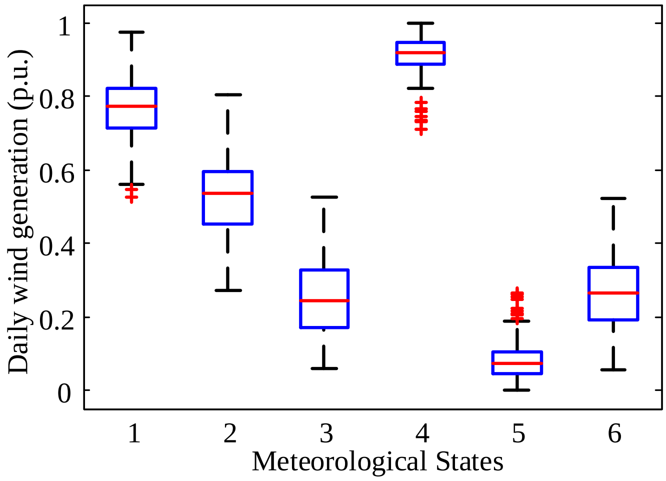


Fig. 3. Box-plot of the daily wind power generation associated to each meteorological state.

The boxplot of the six data subsets is shown in Fig. 3. It can be seen that the daily wind power generation can be effectively distinguished by the meteorological states which are classified by the improved FCM algorithm. There is almost no overlapping among the distribution ranges of the daily wind power generation except State 3 and State 6. Furthermore, the seasonal variations of wind generation can be also obviously distinguished in Table 2. For example, State 1, State 2 and State 3 account for a big proportion among all these states in January. However, State 5 and State 6 account for a big proportion in July.

Table 2

The proportions of meteorological states for each month.

Month	Proportion of Different Meteorological States					
	State 1	State 2	State 3	State 4	State 5	State 6
1	0.2556	0.2444	0.3556	0.1111	0.0333	0
2	0.2099	0.2593	0.3827	0.0741	0.0741	0
3	0.1444	0.2778	0.2778	0.0889	0.2111	0
4	0.2184	0.1954	0.1379	0.0805	0.0920	0.2759
5	0.0667	0.3333	0.0222	0.0111	0.2444	0.3222
6	0.0460	0.2184	0	0	0.2414	0.4943
7	0.0444	0.1778	0	0.0111	0.2778	0.4889
8	0.0444	0.1000	0	0	0.4222	0.4333
9	0.0230	0.2759	0	0.0115	0.3793	0.3103
10	0.0778	0.2667	0.0889	0.0778	0.2333	0.2556
11	0.1264	0.3563	0.1609	0.1264	0.1494	0.0805
12	0.3222	0.2222	0.3111	0.1000	0.0333	0.0111

5.2 Validation and discussion of the proposed model

1) Wind speed with 10-min temporal resolution

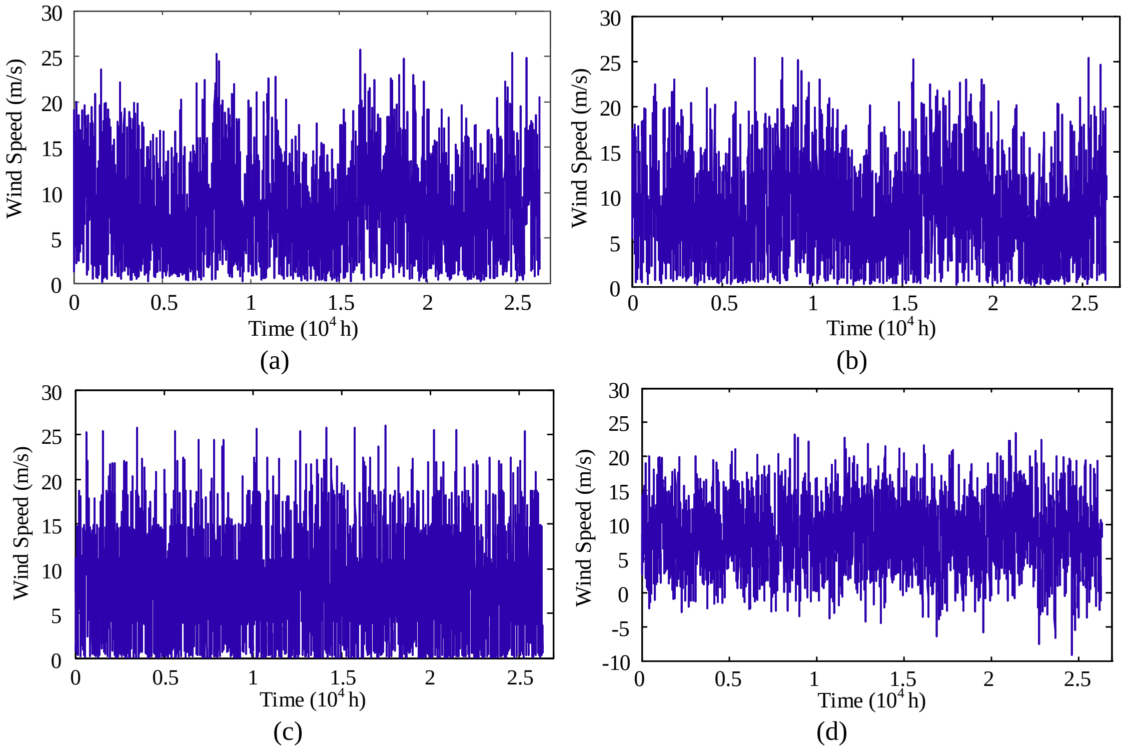


Fig. 4. Wind speed samples generated by different methods. (a) Historical data; (b) The proposed model; (c) MCMC model; (d) ARMA model.

Fig. 4 shows the three-year wind speed samples generated by different models. It can be seen that the MCMC model and ARMA without considering the meteorological and seasonal factors cannot accurately represent the characteristics of wind speed with a long time window. However, the samples generated by the proposed model are quite similar to the historical wind speed data. And the ARMA model may generate some negative wind speed samples (2.59% in this case).

Fig. 5 shows the PDF and ACF curves of the wind speed samples, respectively and Table 4 lists the RMSE indices. It can be seen from Fig. 5(a) and Table 3 that the PDF of simulated data using the proposed model are more accurate than those using the MCMC model and ARMA model. The RMSE indices of the MCMC model and ARMA model are 8 and 6 times that of the proposed model.

It can be seen from the Fig. 5(b) that the auto-correlation of wind speed samples generated by the MCMC model and ARMA model are relatively lower than the measured values. The simulated wind speed samples obtained using the proposed model has a higher auto-correlation. In the time lag ranges of [0, 10] h, the three models have similar characteristics and all perform well in accurately replicating the auto-correlation of wind speed with 10-min time resolution. In the time lag ranges of [10, 40] h, the ARMA model performs better. When the time lag is more than 40 h, the proposed model fits better for the ACF due to the consideration of meteorological factors and seasonal variations. It can be observed from Table 3 that the overall accuracy of the proposed model and ARMA model is better than the MCMC model in terms of ACF.

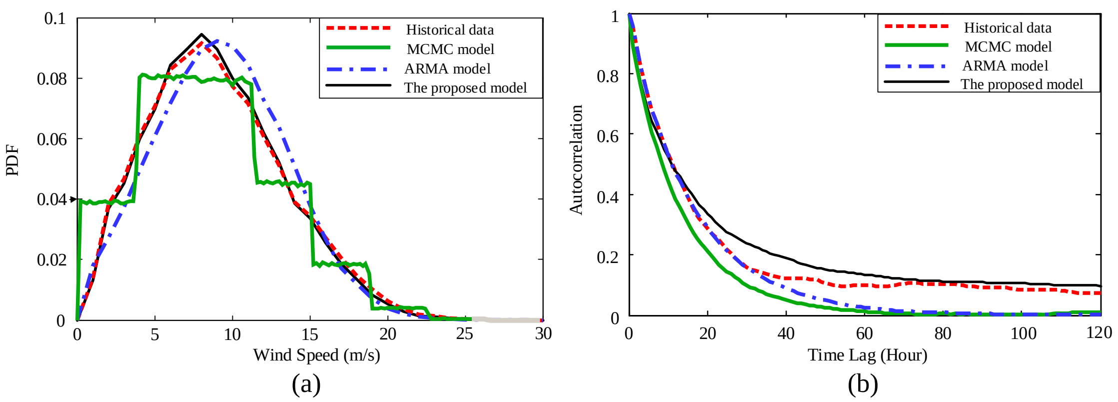


Fig. 5. PDF and ACF curves of wind speed. (a) PDF ;(b) ACF .

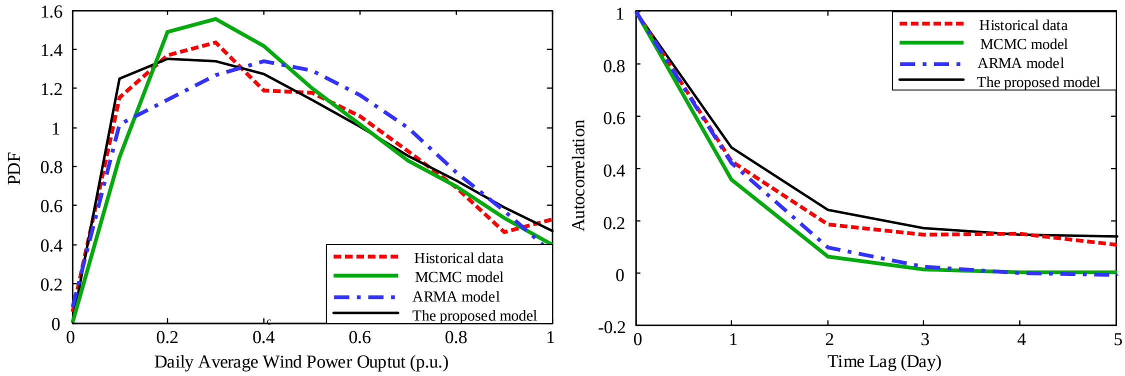
Table 3

The RMSE indices of PDF and ACF using different wind speed models

RMSE	MCMC model	ARMA model	The proposed model
RMSE(PDF)	0.0093	0.0075	0.0012
RMSE(ACF)	0.1019	0.0634	0.0541

2) Daily average wind power output

The PDF and ACF curves of daily average wind power output generated by different models are shown in Fig. 6. It can be seen from Fig. 6(a) that the proposed model performs much better in replicating the PDF of daily average wind power output. It can be seen from Fig.6 (b) that the proposed model also significantly outperforms the other two models in terms of ACF especially in the time lag range of more than one day. It is because the proposed model can capture the characteristics of meteorological state transition process whereas the other two models cannot. The ACF obtained using the MCMC model and ARMA model are lower than the actual measurements.



(a) (b)

Fig. 6. PDF and ACF curves of daily average wind power output. (a) PDF; (b) ACF.

6. Adequacy assessment

In this section, the proposed wind speed model are applied on IEEE-RTS79 [20] and IEEE RTS96 [21] to demonstrate the effectiveness and accuracy of the proposed model for adequacy assessment.

6.1 Adequacy assessment with IEEE-RTS79

The IEEE-RTS79 with wind power is utilized to demonstrate the effectiveness of the proposed wind speed model for adequacy assessment. A 300 MW wind farm is added to the IEEE-RTS79. The power curve of the V80-2.0 MW wind turbine from Vestas are with cut-in, rated, and cut-out wind speeds of 4, 12, and 25 m/s, respectively. The failure rate and repair time of all wind turbine generators are 2 times/year and 44 h, respectively [19]. The sequential Monte-Carlo method (SMCS) is used for assessment. The sample size is 10, 000 years. The loss of load expectation (LOLE) and loss of energy expectation (LOEE) indices obtained using the different wind speed models are listed in Table 4.

Table 4

Reliability indices using different wind speed models

Model	LOLE (h/year)	LOEE (MWh/year)
MCMC model	**4.8535** (19.61%)	**577.64** (20.94%)
ARMA model	**4.6914** (15.61%)	**551.48** (15.47%)
The proposed model	**4.0784** (0.51%)	**481.85** (0.89%)
Historical data	**4.0578**	**477.61**

In Table 4, the bolded numbers are the actual values of reliability indices and the corresponding relative errors are given in the parentheses after them. It can be seen that the LOLE and LOEE indices obtained using the MCMC model and ARMA model are significantly larger than those obtained using the historical data, whereas the indices obtained using the proposed model are close to those obtained using the historical data. The relative errors of the indices obtained using the proposed model is less than 1%, which means that the proposed model is accurate enough for adequacy assessment.

Fig. 7 shows the LOLE and LOEE indices obtained using these different models in spring, summer, autumn, and winter, respectively. It can be observed that the indices obtained using different models have significant differences in winter. It is because the wind speed and power load are both relatively high in winter. Consequently, the effects of wind speed models are much more significant.

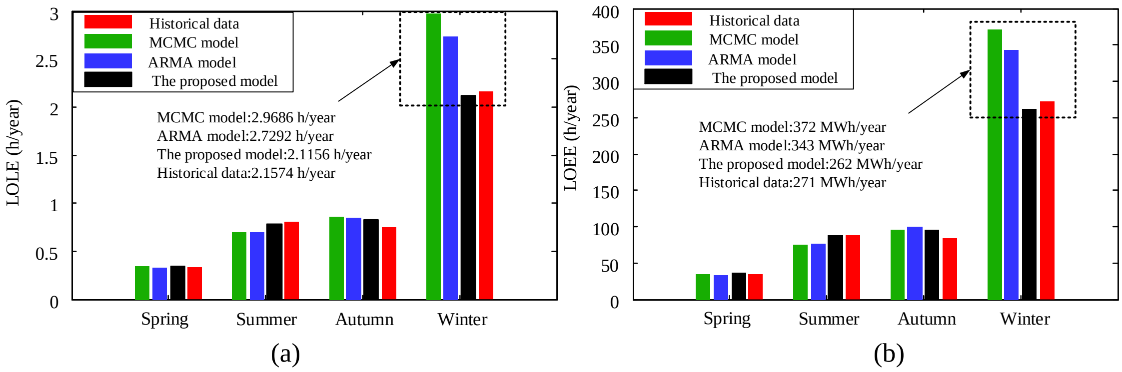


Fig. 7. Reliability indices in different seasons. (a) LOLE. (b) LOEE.

6.2 Adequacy assessment with IEEE-RTS96

A 500 MW wind farm is added to the IEEE-RTS96. Fig. 8 shows the LOLE and LOEE indices of the IEEE-RTS96 with different peak load levels. It can be seen that the all the three models are effective for the adequacy studies, whereas the proposed model shows better accuracy than the MCMC model and ARMA model. Table 5 shows the computation time of the adequacy assessment with different models. The computation efficiency of the proposed model is slightly lower than that of the traditional MCMC model and ARMA model. However, considering the better accuracy, the proposed model is better for offline implementation. Moreover, as can be seen from Table 6, the proposed method has a smaller coefficient variation [13], which implies that adopting the proposed method can speed up the convergence of the simulation.

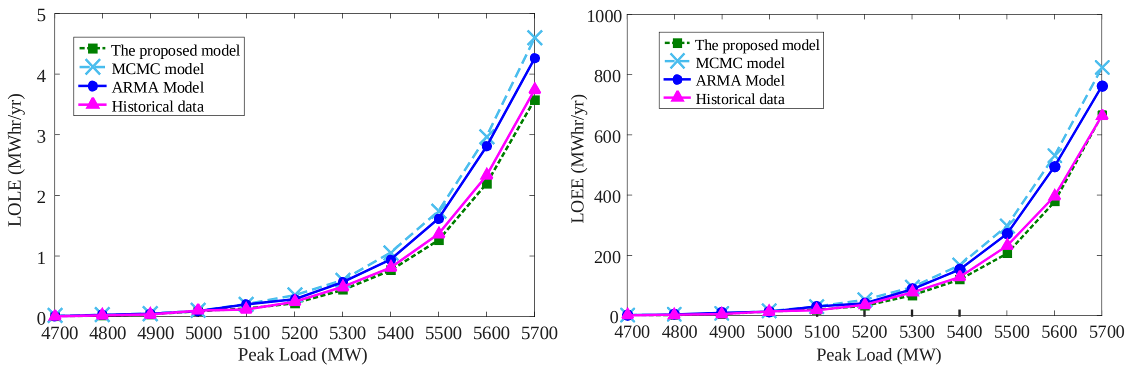


Fig. 8. Reliability indices with different peak load levels. (a) LOLE. (b) LOEE.

Table 5

Computation time for IEEE-RTS96.

Model	MCMC model	ARMA model	The proposed model
Computation Time (s)	885	1164	1216

Table 6

Coefficients variation for IEEE-RTS96.

Model	MCMC model	ARMA model	The proposed model
Coefficient variation	0.067511	0.072114	0.053716

7. Conclusion

The paper proposes a wind speed model considering the meteorological and seasonal factors. The multi-dimensional meteorological vectors are modified by the influence weights firstly. Then, the meteorological vectors are classified into several states using the clustering technique. Based on the Markov Chain, a two-step wind speed model is established considering the meteorological state and wind speed state transition.

Compared with the traditional MCMC model and ARMA model, the proposed model performs better in replicating the wind speed characteristics including the probability distribution and temporal autocorrelation although it needs additional meteorological information. Besides, the practical value of the proposed model is demonstrated by applying to the adequacy assessment. Adopting the proposed model provides more accurate reliability assessment results and shows better convergence performance, which will help the planners and operators better evaluate the power systems with wind power.

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